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Bivariate adjustments for interplot competition in variety trials

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SUMMARY

Bivariate models are proposed to adjust for interplot competition in crop variety trials. The models include competition effects related to the variables of the models and take account of the correlation between these variables. Parameters are estimated by maximum likelihood. The bivariate adjustments are tested using data for yield and plant height from an experiment aimed at studying competition in winter wheat variety trials. In this experiment, they reduced bias due to competition but were not more efficient than univariate height adjustments.

KEY WORDS: competition, interference, likelihood.

1. Introduction

Crop variety trials are carried out by plant breeders and regulatory agencies to select varieties with high performance. These trials are conducted with small plots to reduce costs. However, observations may then be affected by competition between the varieties grown on adjacent plots. Neighbouring varieties may compete for resources such as light, nutrients or moisture. For grain crops, interplot competition has often been found to be due to a competition for light and to be related to plant height (Foucteau et al., 2000; Talbot et al., 1995). In this case, the yield of a variety is lower when the variety is between taller varieties than when it is between shorter varieties. For root crops, competition effects proportional to the yields of neighbouring plots have been observed (Connolly et al., 1993; Kempton, 1982). Competition is a source of bias for variety comparisons and so needs to be controlled as well as possible.

Bias due to competition may be reduced by using plots with unharvested border rows. Competition may also be taken into account using an appropriate experimental design or statistical model (Kempton, 1997). Standard models for competition include models with competition effects proportional to the differences in height between neighbouring varieties or proportional to the yields of neighbouring varieties (Besag and Kempton, 1986; Durban et al., 2000; Kempton and Lockwood, 1984).

In this paper, bivariate models adapted to competition are proposed. These models include competition effects related to the variables of the models and take account of the correlation between these variables. After presenting the models, we describe how to calculate the maximum likelihood estimates of the parameters. The efficiency of the bivariate adjustments is then assessed using data for yield and plant height from a field experiment on wheat.

2. Models

Five models are considered for the analysis of a variety trial with v varieties, b complete blocks, n plots, and two variables measured on each plot. Model 1 is the standard univariate model which ignores competition

$$\mathbf{y}_1 = \mathbf{B}\boldsymbol{\eta}_1 + \mathbf{X}\boldsymbol{\tau}_1 + \boldsymbol{\varepsilon}_1,$$

where $\mathbf{y}_1$ is the vector of observations for the first variable, $\mathbf{B}$ and $\mathbf{X}$ are the design matrices for blocks and varieties, $\boldsymbol{\eta}_1$ and $\boldsymbol{\tau}_1$ are the vectors of block means and centred variety effects, and $\boldsymbol{\varepsilon}_1$ is a vector of random errors which is assumed to follow a normal distribution with expectation zero and variance $\mathbf{Var}(\boldsymbol{\varepsilon}_1) = \sigma_1^2\mathbf{I}_n$, where $\mathbf{I}_n$ denotes the identity matrix of order n.

Model 2 is a standard model for competition. It is univariate and takes account of competition effects which are proportional to the differences in the second variable between neighbouring plots

$$\mathbf{y}_1 = \mathbf{B}\boldsymbol{\eta}_1 + \mathbf{X}\boldsymbol{\tau}_1 + \lambda_{12}\mathbf{W}\mathbf{y}_2 + \boldsymbol{\varepsilon}_1,$$

where λ_{12} is a competition parameter, $\mathbf{y}_2$ is the vector of observations for the second variable, and $\mathbf{W}$ is a $n \times n$ weight matrix. When plots form a single line, $\mathbf{W}$ has the diagonal elements equal to -1, the off-diagonal elements $(i, i \pm 1)$ equal to 0.5 and the other elements equal to zero. The components of $\boldsymbol{\tau}_1$ can be interpreted as pure stand effects, which correspond to the effects of varieties when they have themselves as neighbours.

In this paper, three bivariate models are proposed to adjust for competition. Model 3 is the most general and is equal to

$$\begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \end{bmatrix} = \begin{bmatrix} \mathbf{B} & \mathbf{0} \\ \mathbf{0} & \mathbf{B} \end{bmatrix} \begin{bmatrix} \eta_1 \\ \eta_2 \end{bmatrix} + \begin{bmatrix} \mathbf{X} & \mathbf{0} \\ \mathbf{0} & \mathbf{X} \end{bmatrix} \begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix} + \begin{bmatrix} \lambda_{11}\mathbf{W} & \lambda_{12}\mathbf{W} \\ \lambda_{21}\mathbf{W} & \lambda_{22}\mathbf{W} \end{bmatrix} \begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix},$$

or concisely

$$\mathbf{y} = \mathbf{T}\boldsymbol{\theta} + (\boldsymbol{\Lambda} \otimes \mathbf{W})\mathbf{y} + \boldsymbol{\varepsilon}, \tag{1}$$

where

$$\mathbf{y} = \begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \end{bmatrix}$$

is the $2n$-vector of observations of the first and second variable, $\mathbf{T} = [\mathbf{I}_2 \otimes \mathbf{B} \mid \mathbf{I}_2 \otimes \mathbf{X}]$ is a $2n \times (2b + 2v)$ design matrix and $\otimes$ denotes the Kronecker product,

$$\Theta = \begin{bmatrix} \eta_1 \\ \eta_2 \\ \tau_1 \\ \tau_2 \end{bmatrix}$$

is a $(2b + 2v)$-vector of block means ($\boldsymbol{\eta}$) and variety pure stand effects ($\boldsymbol{\tau}$),

$$\Lambda = \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{bmatrix}$$

is the matrix of competition parameters,

$$\boldsymbol{\varepsilon} = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix}$$

is a $2n$-vector of random errors, which is assumed to follow a normal distribution with expectation zero and variance

$$\text{Var}(\boldsymbol{\varepsilon}) = \mathbf{V} = \begin{bmatrix} \sigma_1^2 & \rho \\ \rho & \sigma_2^2 \end{bmatrix} \otimes \mathbf{I}_n.$$

In Model 4, the competition affecting a variable is due to the differences in this variable only, and therefore $\boldsymbol{\Lambda}$ has the form

$$\boldsymbol{\Lambda} = \begin{bmatrix} \lambda_{11} & 0 \\ 0 & \lambda_{22} \end{bmatrix}.$$

In Model 5, competition effects are related to the differences in the second variable only. In this case, the matrix $\boldsymbol{\Lambda}$ is equal to

$$\boldsymbol{\Lambda} = \begin{bmatrix} 0 & \lambda_{12} \\ 0 & \lambda_{22} \end{bmatrix}.$$

3. Analysis

The analyses are similar for Models 3-5, so we describe the analysis for Model 3 only. We extend the methods used by Besag and Kempton (1986) and estimate parameters by the method of maximum likelihood. Equation (1) can be written as

$$\mathbf{y} = \mathbf{G}^{-1}\mathbf{T}\boldsymbol{\theta} + \mathbf{G}^{-1}\boldsymbol{\varepsilon}, \tag{2}$$

where $\mathbf{G} = \mathbf{I}_{2n} - (\boldsymbol{\Lambda} \otimes \mathbf{W})$ is assumed to be non-singular. The expectation and variance of $\mathbf{y}$ are equal to

$$\mathbf{E}(\mathbf{y}) = \mathbf{G}^{-1}\mathbf{T}\boldsymbol{\theta}, \qquad \mathbf{Var}(\mathbf{y}) = \mathbf{G}^{-1}\mathbf{V}(\mathbf{G}^{-1})'.$$

The log-likelihood of Model 3 is equal to

$$\begin{aligned}\mathbf{l}(\boldsymbol{\theta}, \mathbf{V}, \boldsymbol{\lambda}) = \quad & -n\ln(2\pi) - \ln(|\ \mathbf{G}^{-1}\mathbf{V}(\mathbf{G}^{-1})'\ |)/2 - \\ & (\mathbf{y} - \mathbf{G}^{-1}\mathbf{T}\boldsymbol{\theta})'(\mathbf{G}^{-1}\mathbf{V}(\mathbf{G}^{-1})')^{-1}(\mathbf{y} - \mathbf{G}^{-1}\mathbf{T}\boldsymbol{\theta})/2,\end{aligned} \tag{3}$$

where $\boldsymbol{\lambda}$ denotes the vector of the four parameters of $\boldsymbol{\Lambda}$. It can be written as

$$\mathbf{l}(\boldsymbol{\theta}, \mathbf{V}, \boldsymbol{\lambda}) = \ln(|\ \mathbf{G}^2\ |)/2 - \ln(|\ \mathbf{V}\ |)/2 - (\mathbf{G}\mathbf{y} - \mathbf{T}\boldsymbol{\theta})'\mathbf{V}^{-1}(\mathbf{G}\mathbf{y} - \mathbf{T}\boldsymbol{\theta})/2 + \textit{constant}.$$

For a given $\boldsymbol{\lambda}$, the maximum likelihood estimator of $\boldsymbol{\theta}$ is equal to

$$\widehat{\boldsymbol{\theta}}_\lambda = (\mathbf{T}'\mathbf{T})^{-}\mathbf{T}'\mathbf{G}\mathbf{y}, \tag{4}$$

where ($\mathbf{T}'\mathbf{T}$)- denotes a generalised inverse of $\mathbf{T}'\mathbf{T}$ chosen so that the estimators of variety effects have zero mean. The estimators of the parameters of $\mathbf{V}$ for a given $\boldsymbol{\lambda}$ are equal to

$$\hat{\sigma}^2_{1\lambda} = \mathbf{z}_1'\mathbf{Q}\mathbf{z}_1/rdf, \quad \hat{\sigma}^2_{2\lambda} = \mathbf{z}_2'\mathbf{Q}\mathbf{z}_2/rdf, \quad \hat{\rho}_\lambda = \mathbf{z}_1'\mathbf{Q}\mathbf{z}_2/rdf,$$

where

$$\begin{aligned}\mathbf{z}_1 &= (\mathbf{I}_n - \lambda_{11}\mathbf{W})\mathbf{y}_1 - \lambda_{12}\mathbf{W}\mathbf{y}_2, \\ \mathbf{z}_2 &= -\lambda_{21}\mathbf{W}\mathbf{y}_1 + (\mathbf{I}_n - \lambda_{22}\mathbf{W})\mathbf{y}_2, \\ \mathbf{Q} &= \mathbf{I}_n - (\mathbf{B} \mid \mathbf{X})[(\mathbf{B} \mid \mathbf{X})'(\mathbf{B} \mid \mathbf{X})]^{-}(\mathbf{B} \mid \mathbf{X})', \\ rdf &= n - v - b + 1.\end{aligned} \tag{5}$$

The vector $\boldsymbol{\lambda}$ may be estimated by replacing $\boldsymbol{\theta}$ and $\mathbf{V}$ in (3) by their estimators (4) and (5) and by maximising the profile log-likelihood (Murphy and van der Vaart, 2000)

$$\mathbf{pl}(\boldsymbol{\lambda}) = \mathbf{l}(\hat{\boldsymbol{\theta}}_\lambda, \hat{\mathbf{V}}_\lambda, \boldsymbol{\lambda}) = \ln(|\ \mathbf{G}^2\ |)/2 - \ln(|\ \hat{\mathbf{V}}_\lambda\ |)/2 + \ \textit{constant}.$$

Assuming that $\mathbf{I}_n - \lambda_{11}\mathbf{W}$ or $\mathbf{I}_n - \lambda_{22}\mathbf{W}$ is not singular, the profile log-likelihood can be written as

$$\mathbf{pl}(\boldsymbol{\lambda}) = \sum_{i=1}^{n} \ln[((1-\lambda_{11}\gamma_i)(1-\lambda_{22}\gamma_i)-\lambda_{12}\lambda_{21}\gamma_i^2)^2]/2 - n\ln(\hat{\sigma}_{1\lambda}^2\hat{\sigma}_{2\lambda}^2-\hat{\rho}_{\lambda}^2)/2 + \textit{constant},$$

where γ_i is the i-th eigenvalue of $\mathbf{W}$. We maximised this log-likelihood numerically using the function FindMinimum of Mathematica® and the function nlminb of S-PLUS®. The vector $\boldsymbol{\theta}$ and $\mathbf{V}$ are estimated by inserting the estimate of $\boldsymbol{\lambda}$ into (4) and (5).

The variance of $\hat{\boldsymbol{\lambda}}$ may be estimated from the curvature of the profile log-likelihood (Murphy and van der Vaart, 2000)

$$\widehat{\mathbf{Var}}(\hat{\boldsymbol{\lambda}}) = \left(-\frac{\partial^2 \mathbf{pl}}{\partial\boldsymbol{\lambda}\partial\boldsymbol{\lambda}'}(\hat{\boldsymbol{\lambda}})\right)^{-1}.$$

The nullity of $\boldsymbol{\lambda}$ can be tested using twice the logarithm of the profile likelihood ratio, i.e. $2\left(\mathbf{pl}(\hat{\boldsymbol{\lambda}}) - \mathbf{pl}(\mathbf{0}_4)\right)$, where $\mathbf{0}_4$ denotes the null vector of size four (Murphy and van der Vaart, 2000). This statistic follows approximately a χ^2 distribution with four degrees of freedom.

4. Analysis of a field experiment on winter wheat

The efficiency of the bivariate models to adjust for competition was assessed using a field experiment carried out to study interplot competition in winter wheat variety trials. The experiment was conducted by the Institut Technique des Céréales et des Fourrages near Melun in France in 1993. Three trials were carried out in this experiment. Trials 1 and 2 had plots with six seeded and harvested rows. In the third trial, plots had eleven seeded rows and only the seven central rows were harvested. This trial was called the reference trial because competition was expected to be low on the harvested rows. The same seven varieties were used in the three trials. They had large differences for characters expected to be related to competition such as plant height. Each trial had six complete blocks. Each block was a line of plots with a border plot on either side and blocks were separate. A standard randomisation was used in Trial 1 and the reference trial. Trial 2 was a neighbour-balanced design where each variety had each other variety as neighbour the same number of times (Azaïs et al., 1993). Yield, the main variable, and final plant height were measured on each plot.

Models 1 and 2 were applied to yield. For Models 3-5, yield was the first variable and plant height was the second variable. Only the data from non-border plots were analysed. Models 2-5 were extended to cope with border plots and separate blocks as follows. Consider Model 3 for example. The matrix $\mathbf{W}$ was taken equal to $\mathbf{W} = \mathbf{I}_b \otimes \mathbf{U}$, where $\mathbf{U}$ is the $v \times v$ matrix having the diagonal elements equal to -1, the off-diagonal elements $(i, i \pm 1)$ equal to 0.5 and the other elements equal to zero. The term $(\mathbf{\Lambda} \otimes \mathbf{I}_n)(\mathbf{c}_1' \mathbf{c}_2')'$ was included in the model, where $\mathbf{c}_1$ was a covariate of size n equal to half of the yield of the adjacent border plot for the first and last observations of each block and to zero otherwise, and $\mathbf{c}_2$ was the corresponding covariate for height. The components of $\mathbf{c}_1$ and $\mathbf{c}_2$ were considered as fixed.

The estimates of the competition parameters for Models 4 and 5 suggest that a competition related to yield and height affected yield in the six-row-plot trials (Tables 1 and 2). However, the correlation between the yield and height differences between neighbouring plots was equal to 0.93 in Trial 1 and to 0.89 in Trial 2. Thus, competition effects due to yield and height differences were confounded for a large part. This may explain why the estimates of λ_{12} showed large differences for Models 3 and 5. The correlation between the estimates of λ_{11} and λ_{12} in Model 3 was estimated by –0.88 in Trial 1 and by –0.83 in Trial 2. Although Model 5 took account of the correlation between yield residuals and height residuals, Models 2 and 5 led to similar estimates of λ_{12}. The estimates of the parameters related to the competition affecting height were larger (in absolute value) than twice their standard errors for Model 3 and Trial 2, but not in the other cases. The models did not give consistent estimates of the correlation between yield and height residuals.

The estimates of yield variety effects in the six-row-plot trials were compared to the reference estimates obtained from the reference trial and Model 1. The criterion used to compare variety estimates was the standard deviation of the seven differences $\tau_{1i}^{+} - \tau_{1i}^{*}$, where τ_{1i}^{+} is the estimate of the yield effect of variety i given by a six-row-

Table 1. Estimates of competition parameters and estimates of the correlation between yield residuals and height residuals in Trial 1 using Models 2-5

Competition	Model			
parameters‡	2	3	4	5
λ_{11}		$-0.26 \pm 0.05^{\dagger}$	-0.31 ± 0.03	
λ_{12}	-0.04 ± 0.01	-0.01 ± 0.01		-0.04 ± 0.01
λ_{21}		0.97 ± 0.70		
λ_{22}		-0.08 ± 0.10	0.04 ± 0.05	0.04 ± 0.05
χ^2 value		41.91**	39.65**	30.79**
Correlation		0.03	−0.01	−0.35

** Significant at the 0.01 level of probability

† Estimate and standard error

‡ Yield is expressed in Mg/ha and height is expressed in cm

Table 2. Estimates of competition parameters and estimates of the correlation between yield residuals and height residuals in Trial 2 using Models 2-5

Competition	Model			
parameters[‡]	2	3	4	5
λ_{11}		$-0.22 \pm 0.06^{\dagger}$	-0.29 ± 0.03	
λ_{12}	-0.03 ± 0.01	-0.01 ± 0.01		-0.03 ± 0.01
λ_{21}		1.26 ± 0.54		
λ_{22}		-0.17 ± 0.06	-0.04 ± 0.03	-0.04 ± 0.03
χ^2 value		38.45**	32.87**	25.35**
Correlation		0.37	0.28	−0.11

** Significant at the 0.01 level of probability

† Estimate and standard error

‡ Yield is expressed in Mg/ha and height is expressed in cm

plot trial and a model, and τ^*_{1i} is the yield reference estimate of variety i. Models 2-5 reduced bias due to competition in the six-row-plot trials, but Models 3-5 were not more efficient than Model 2 (Tables 3 and 4).

Models 2 and 3 were applied to the reference trial. As the first replicate of this trial had a missing value, the analyses were carried out using the last five replicates. The estimates of the competition parameters were equal to $\hat{\lambda}_{12} = 0 \pm 0.01$ (Mg/ha)/cm for Model 2, $\hat{\lambda}_{11} = 0.01 \pm 0.08$ (Mg/ha)/(Mg/ha), $\hat{\lambda}_{12} = 0 \pm 0.01$ (Mg/ha)/cm,

Table 3. Estimates of yield variety effects (Mg/ha) in Trial 1 using Models 1-5 and comparison with the reference estimates

Variety effects	Reference estimates[†]	Model 1	2	3	4	5
Apollo (90)[‡]	0.37	1.17	0.38	0.56	0.65	0.31
Scipion (75)	0.28	−0.05	−0.11	−0.07	−0.06	−0.11
Soissons (73)	0.25	0.44	0.37	0.19	0.17	0.36
Beaver (72)	0.19	−0.06	0.27	0.15	0.11	0.31
Thésée (77)	0.16	−0.29	−0.09	−0.10	−0.12	−0.07
Eureka (86)	0.05	0.56	0.15	0.21	0.26	0.11
Courtot (60)	−1.30	−1.77	−0.98	−0.94	−1.00	−0.90
Standard deviation[§]		0.50	0.24	0.25	0.26	0.26

[†]Estimates of yield variety effects obtained using the reference trial and Model 1.

[‡]Average height in cm in the reference trial

[§]Standard deviation of the differences in variety estimates with the reference estimates

Table 4. Estimates of yield variety effects (Mg/ha) in Trial 2 using Models 1-5 and comparison with the reference estimates

Variety effects	References estimates†	Model				
		1	2	3	4	5
Apollo (90)‡	0.37	0.98	0.43	0.52	0.60	0.42
Scipion (75)	0.28	−0.23	−0.24	−0.17	−0.15	−0.24
Soissons (73)	0.25	0.28	0.32	0.23	0.20	0.32
Beaver (72)	0.19	0.04	0.25	0.10	0.03	0.25
Thésée (77)	0.16	0.11	0.15	0.11	0.09	0.15
Eureka (86)	0.05	0.50	0.14	0.20	0.26	0.13
Courtot (60)	−1.30	−1.68	−1.05	−0.99	−1.03	−1.03
Standard deviation§		0.41	0.24	0.24	0.25	0.25

†Estimates of yield variety effects obtained using the reference trial and Model 1.

‡Average height in cm in the reference trial

§Standard deviation of the differences in variety estimates with the reference estimates

$\hat{\lambda}_{21} = -0.50 \pm 0.75$ cm/(Mg/ha), $\hat{\lambda}_{22} = 0.07 \pm 0.08$ cm/cm for Model 3, $\hat{\lambda}_{11} = -0 \pm 0.02$ (Mg/ha)/(Mg/ha), $\hat{\lambda}_{22} = 0.02 \pm 0.02$ cm/cm for Model 4, and to $\hat{\lambda}_{12} = -0 \pm 0.01$ (Mg/ha)/cm, $\hat{\lambda}_{22} = 0.02 \pm 0.02$ cm/cm for Model 5. These results suggest that competition was low in the reference trial.

5. Discussion

Maximum likelihood estimates may be biased for the competition models considered. Durban et al. (2000) found that the methods of adjusted profile likelihood reduced this bias for a univariate model. Similar investigations could be performed for the bivariate models.

When observations are independent and identically distributed, maximum likelihood estimators are asymptotically unbiased, efficient, with a normal distribution, and twice the logarithm of the profile likelihood ratio asymptotically follows a chi-squared distribution. As observations are not independent and identically distributed for the bivariate competition models, the standard errors and tests proposed for competition parameters should be considered as approximate. More work could be done to derive the asymptotic distribution of estimators.

In our application, the bivariate adjustments for competition did not perform better than univariate adjustments. It would be interesting to compare these methods of adjustment using other data.

The methods presented in this paper could be extended to take account of more than two variables.

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Dwuzmienna analiza doświadczeń odmianowych z uwzględnieniem efektu konkurencji

STRESZCZENIE

W pracy przedstawiono trzy modele obserwacji, uwzględniające współdziałanie roślin na sąsiadujących poletkach, gdy w doświadczeniu obserwowane są dwie cechy jednocześnie. Zaproponowane modele zawierają efekty konkurencji i biorą pod uwagę skorelowanie obserwowanych cech. Do estymacji parametrów wykorzystano metodę największej wiarogodności. Zaproponowaną teorię zilustrowano przykładem analizy wyników doświadczenia z pszenicą ozimą, w którym badano efekty współzawodnictwa. W analizowanym doświadczeniu zastosowane modele zmniejszyły obciążenie wywołane konkurencją lecz nie okazały się lepsze od analizy kowariancji.

SŁOWA KLUCZOWE: konkurencja, współdziałanie, wiarogodność.